

# Workshop on the ACTS Toolkit

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## TAO – Toolkit for Advanced Optimization

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# Outline

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- ◊ Optimization background
- ◊ TAO
  - Algorithms
  - Interface
  - Usage

## What is Nonlinearly Constrained Optimization?

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$$\min \{f(x) : x_l \leq x \leq x_u, c_l \leq c(x) \leq c_u\}$$

- ◊ Systems of nonlinear equations

$$\min \left\{ \frac{1}{2} \|r(x)\|^2 : x_l \leq x \leq x_u \right\}, \quad r : \mathbb{R}^n \mapsto \mathbb{R}^n$$

- ◊ Nonlinear least squares

$$\min \left\{ \frac{1}{2} \|r(x)\|^2 : x_l \leq x \leq x_u \right\}, \quad r : \mathbb{R}^n \mapsto \mathbb{R}^m, \quad m \geq n$$

- ◊ Bound-constrained optimization

$$\min \{f(x) : x_l \leq x \leq x_u\}$$

## The Ginzburg-Landau Model for Superconductivity

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Minimize the Gibbs free energy for a homogeneous superconductor with a vector potential perpendicular to the superconductor.

$$\int_{\mathcal{D}} \left\{ -|v(x)|^2 + \frac{1}{2} |v(x)|^4 + \|[\nabla - iA(x)] v(x)\|^2 + \kappa^2 \|(\nabla \times A)(x)\|^2 \right\} dx$$

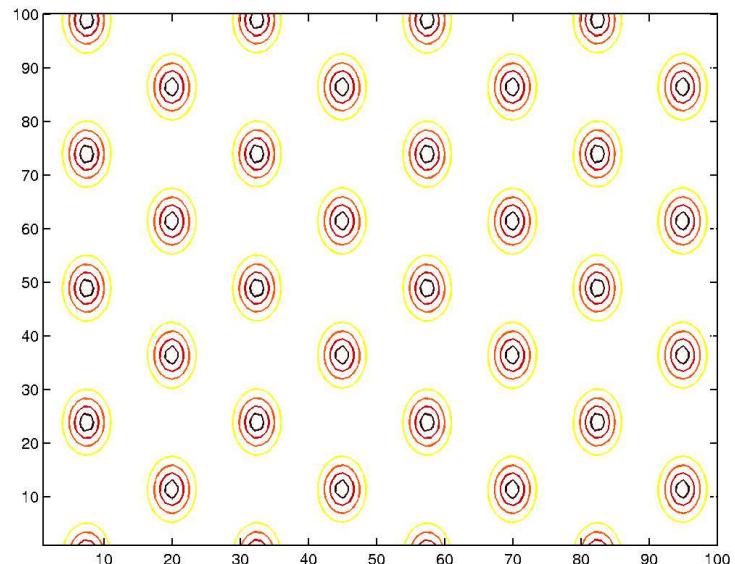
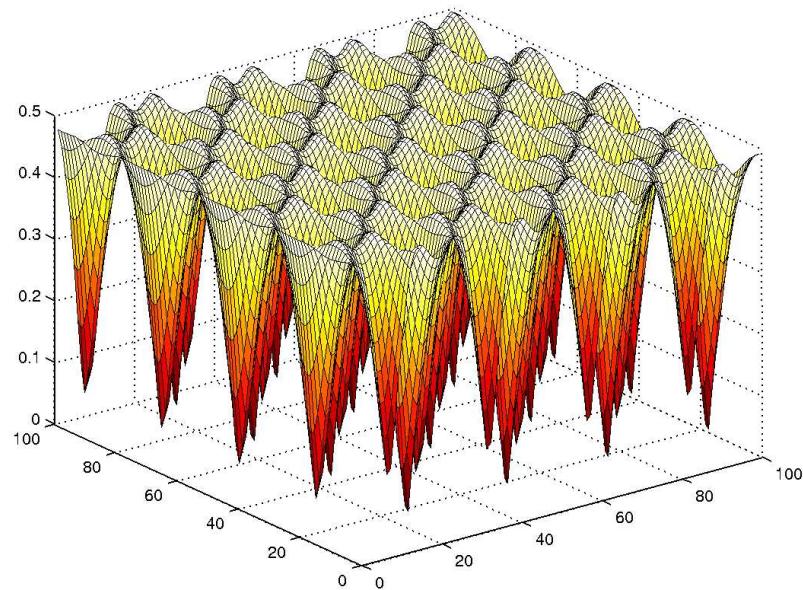
$v : \mathbb{R}^2 \rightarrow \mathbb{C}$  is the order parameter

$A : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  is the vector potential

# The Ginzburg-Landau Model for Superconductivity

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Unconstrained problem. Non-convex function. Hessian is singular.  
Unique minimizer, but there is a saddle point.



## Minimal Surface with Obstacles

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Determine the surface of minimal area and given boundary data that lies above an obstacle.

$$\min \{f(v) : v \in K\}$$

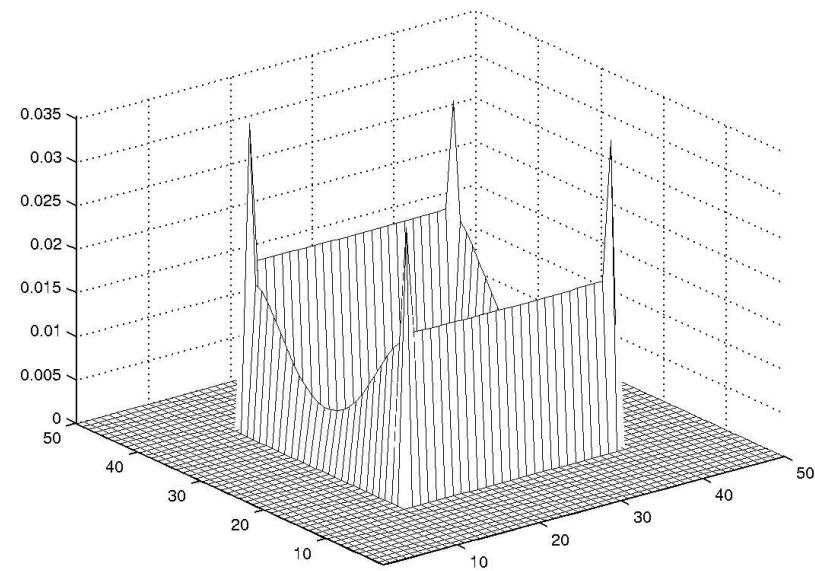
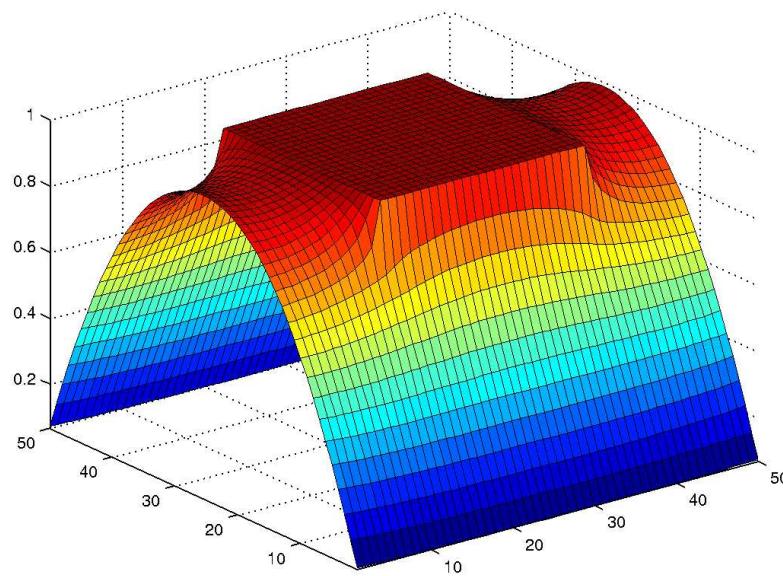
$$f(v) = \int_{\mathcal{D}} \sqrt{1 + \|\nabla v(x)\|^2} \, dx$$

$$K = \{v \in H^1 : v(x) = v_D(x), \ x \in \partial D, \ v(x) \geq v_L(x), \ x \in \mathcal{D}\}$$

## Minimal Surface with Obstacles

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Bound constrained problem. Number of active constraints depends on the height of the obstacle. Almost all multipliers are zero.



## Isomerization of $\alpha$ -pinene

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Determine the reaction coefficients in the thermal isomerization of  $\alpha$ -pinene from measurements by minimizing

$$\sum_{j=1}^8 \|y(\tau_j; \theta) - z_j\|^2,$$

where  $z_j$  are the measurements and

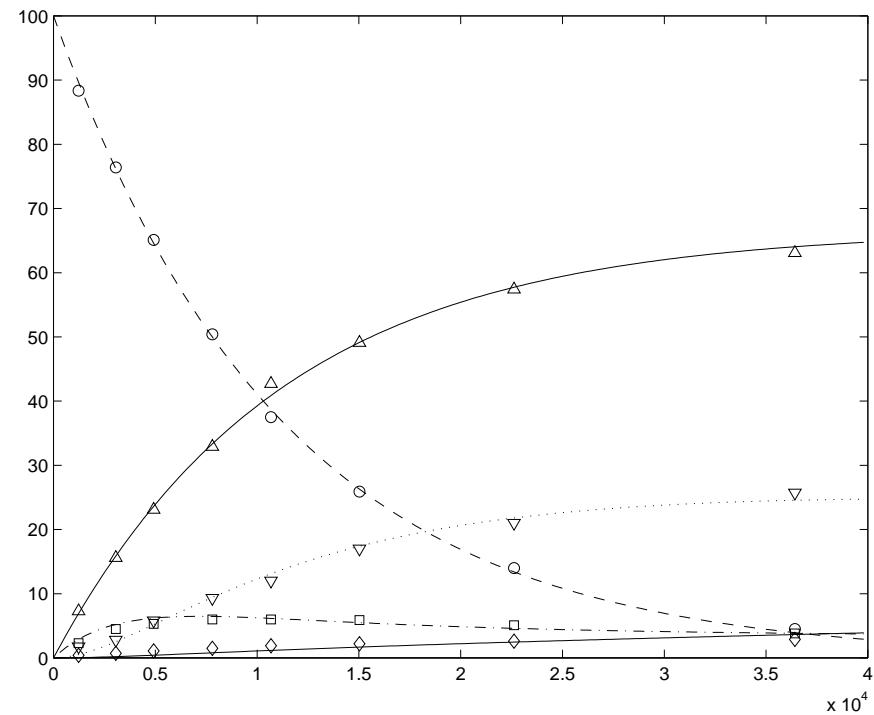
$$\begin{aligned} y'_1 &= -(\theta_1 + \theta_2)y_1 \\ y'_2 &= \theta_1 y_1 \\ y'_3 &= \theta_2 y_1 - (\theta_3 + \theta_4)y_3 + \theta_5 y_5 \\ y'_4 &= \theta_3 y_3 \\ y'_5 &= \theta_4 y_3 - \theta_5 y_5 \end{aligned}$$

## Isomerization of $\alpha$ -pinene

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Only equality constraints. Typical parameter estimation problem.



## Optimization Toolkits

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State-of-the-art in optimization software:

- ◊ Scattered support for parallel computations
- ◊ Little reuse of linear algebra software
- ◊ Minimal use of automatic differentiation software
- ◊ Few object-oriented optimization codes
- ◊ Nonlinear optimization problems with more than 10,000 variables are considered large.

# TAO

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The process of nature by which all things change and which is to be followed for a life of harmony.

## The Right Way

Toolkit for advanced optimization

- ◊ Object-oriented techniques
- ◊ Component-based interaction
- ◊ Leverage of existing parallel computing infrastructure
- ◊ Reuse of external toolkits

## TAO Goals

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- ◊ Portability
- ◊ Performance
- ◊ Scalable parallelism
- ◊ An interface independent of architecture

## TAO Algorithms for Bound-Constrained Optimization

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$$\min \{f(x) : x_l \leq x \leq x_u\}$$

- ◇ Conjugate gradient algorithms
- ◇ Limited-memory variable-metric algorithms
- ◇ Newton algorithms

You must supply the function  $f : \mathbb{R}^n \mapsto \mathbb{R}$  and the gradient

$$\nabla f(x) = (\partial_i f(x))$$

For Newton methods you also need to supply the Hessian matrix.

$$\nabla^2 f(x) = (\partial_{i,j} f(x))$$

## Conjugate Gradient Algorithms

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$$x_{k+1} = x_k + \alpha_k p_k$$

$$p_{k+1} = -\nabla f(x_k) + \beta_k p_k$$

where  $\alpha_k$  is determined by a line search.

Three choices of  $\beta_k$  are possible ( $g_k = \nabla f(x_k)$ ):

$$\beta_k^{FR} = \left( \frac{\|g_{k+1}\|}{\|g_k\|} \right)^2, \quad \text{Fletcher-Reeves}$$

$$\beta_k^{PR} = \frac{\langle g_{k+1}, g_{k+1} - g_k \rangle}{\|g_k\|^2}, \quad \text{Polak-Rivièvre}$$

$$\beta_k^{PR+} = \max \{ \beta_k^{PR}, 0 \}, \quad \text{PR-plus}$$

## Limited-Memory Variable-Metric Algorithms

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$$x_{k+1} = x_k - \alpha_k H_k \nabla f(x_k)$$

where  $\alpha_k$  is determined by a line search.

The matrix  $H_k$  is defined in terms of information gathered during the previous  $m$  iterations.

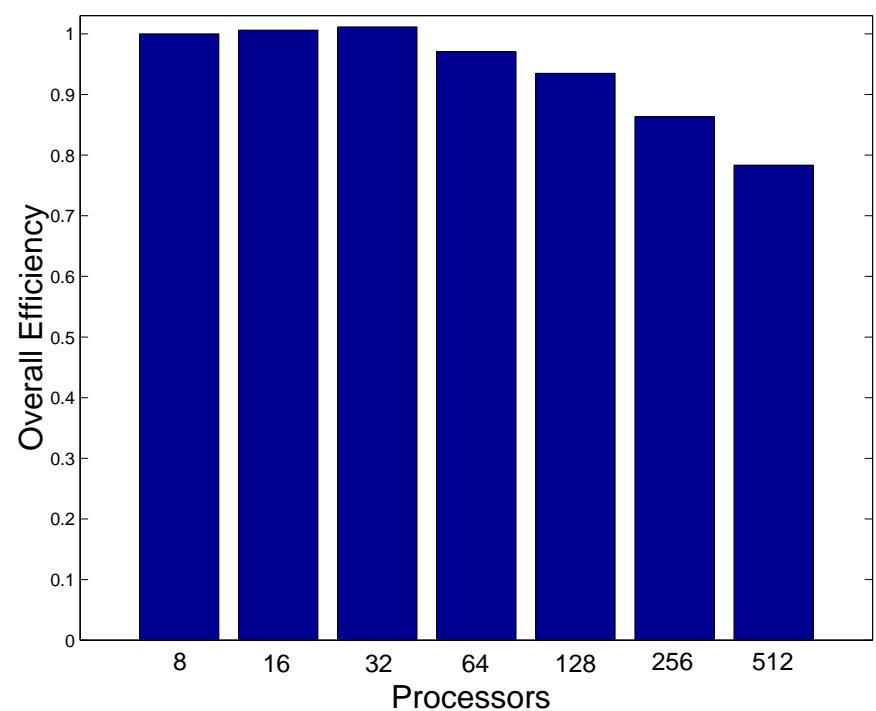
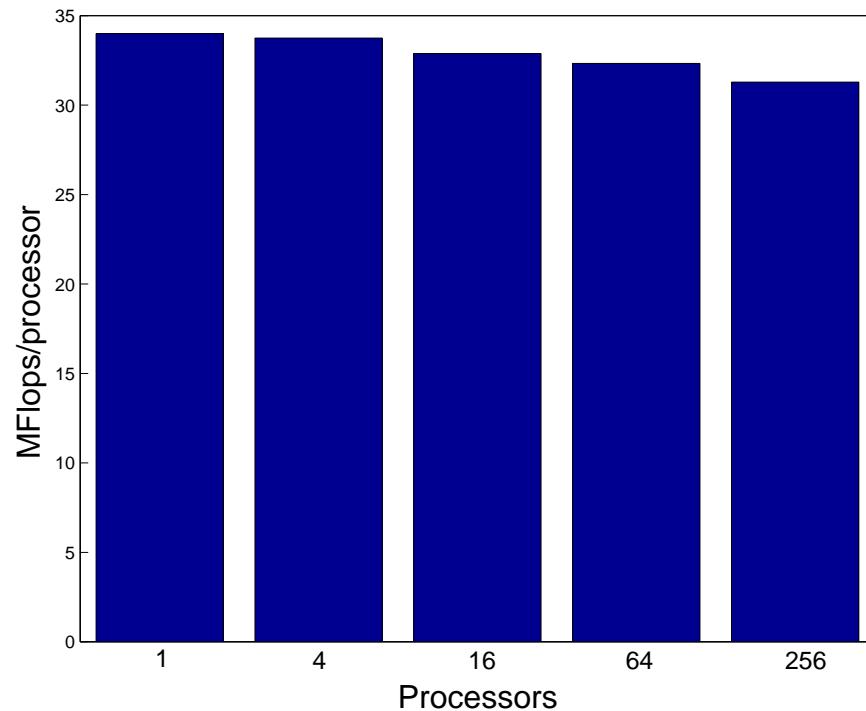
- ◊  $H_k$  is positive definite.
- ◊ Storage of  $H_k$  requires  $2mn$  locations.
- ◊ Computation of  $H_k \nabla f(x_k)$  costs  $(8m + 1)n$  flops.

## TAO Performance: Plate Problem



Cray T3E (NERSC)

$$n = 2.56 \cdot 10^6 \text{ variables}$$



## TAO Algorithms (partial list)

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- ◊ Unconstrained optimization
  - Conjugate gradient algorithms PR, FR, PR+
  - Levenberg-Marquardt method (alpha)
- ◊ Bound-constrained optimization
  - Limited-memory variable-metric algorithm
  - Trust region Newton method
- ◊ Linearly constrained optimization
  - Interior-point quadratic programming method (alpha)
- ◊ Nonlinearly constrained optimization
  - Work in progress

## TAO Interface

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```
TAO_SOLVER tao;                      /* TAO_SOLVER solver context */
Vec      x, g;                      /* solution and gradient vectors */
int      n;                          /* number of variables */
AppCtx   user;                      /* user-defined application context */
TaoVecPetsc *xx,*gg;

VecCreate(MPI_COMM_WORLD,n,&x);
VecDuplicate(x,&g);

TaoWrapPetscVec(x,&xx);
TaoWrapPetscVec(g,&gg);

TaoCreate(xx,'tao_lmvm',0,MPI_COMM_WORLD,&tao);
TaoSetFunctionGradient(tao,&ff,gg,FunctionGradient,(void *)&user);
TaoSolve(tao);

TaoDestroy(tao);
```

## Function Evaluation

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```
typedef struct {           /* Used in the minimum surface area problem */
    int          mx, my;      /* discretization in x, y directions */
    Vec          Bottom, Top, Left, Right; /* boundary values */
} AppCtx;

int FormFunction(TAO_SOLVER tao, TaoVec *xx, double* fcn,void *userCtx){
    AppCtx *user = (AppCtx *)userCtx;
    Vec X;

    TaoVecGetPetscVec(xx,&x);
    ...
    return 0;
}
```

The user sets this routine in the main program via

```
info = TaoSetFunction(tao,&ff,FormFunction,(void *)&user);
```

## Gradient Evaluation

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```
int FormGradient(TAO_SOLVER tao, TaoVec *xx, TaoVec *gg,void *userCtx){  
    AppCtx *user = (AppCtx *)userCtx;  
    Vec X,G;  
  
    TaoVecGetPetscVec(xx,&x);  
    TaoVecGetPetscVec(gg,&g);  
    ...  
    return 0;  
}
```

The user sets this routine in the main program via

```
info = TaoSetGradient(tao,gg,FormGradient,(void *)&user);
```

Alternatively, the user can supply the function and gradient evaluation in a single routine.

A Hessian evaluation routine can be supplied in a similar manner.

## Convergence

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Absolute tolerances specify acceptable errors in the optimality of the function and the constraints.

$$f(x) \leq f(x^*) + \epsilon_{fatol}$$

Relative tolerances specify the number of significant digits required in the solution and the constraints.

$$f(x) \leq f(x^*) + \epsilon_{frtol} |f(x^*)|$$

These tolerance can be changed

```
int TaoSetTolerances(TAO_SOLVER solver,double fatol,double frtol,  
                     double catol,double crtol)
```

## TAO Basic Facilities

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- ◊ TaoInitialize
- ◊ TaoFinalize
- ◊ TaoSetInitialVector
- ◊ TaoSetBounds
- ◊ TaoGetLinearSolver
- ◊ TaoGetIterationData
- ◊ TaoView

## Parallel Functionality

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The TAO interface is the same in a parallel environment, but the user must provide vectors with a parallel structure.

```
VecCreateMPI(MPI_COMM_WORLD,n,PETSC_DECIDE,&x);
VecDuplicate(x,&g);

TaoWrapPetscVec(x,&xx);
TaoWrapPetscVec(g,&gg);
info = TaoCreate(xx,'tao_lmvm',0,MPI_COMM_WORLD,&tao);
info = TaoSetFunctionGradient(tao,ff,gg,FunctionGradient,(void *)&user);
info = TaoSolve(tao);

info = TaoDestroy(tao);
```

The user still provides the routines that evaluate the function and gradient. These routines do not have to be performed in parallel, but parallel evaluations usually improve performance.

## Parallel Function Evaluation

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```
typedef struct {                                     /* For Minimum Surface Area Problem */
    int          mx, my;                         /* discretization in x, y directions */
    Vec          Bottom, Top, Left, Right;        /* boundary values */
    DA           da;                            /* distributed array data structure */
} AppCtx;

int FormFunction(TAO_SOLVER tao, TaoVec *xx, double* fcn,void *userCtx){
    AppCtx *user = (AppCtx *)userCtx;
    Vec x;
    double f=0;
    TaoVecGetPetscVec(xx,&x);
    for (i=xs; i<xe; i++){
        for (j=ys; j<ye; j++){
            f += ...
        }
    }
    info = MPI_Allreduce(&f,fcn,1,MPI_DOUBLE,MPI_SUM,MPI_COMM_WORLD);
    return 0;
}
```

# TAO

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[www.mcs.anl.gov/tao](http://www.mcs.anl.gov/tao)

Version 1.2 (June 2001)

- ◊ Source Code
- ◊ Documentation
- ◊ Installation instructions
- ◊ Example problems
- ◊ Performance results
- ◊ Supported architectures